House prices and neighbourhood amenities: beyond the norm?

Emerald International Journal of Housing Markets and Analysis

House Prices and Neighbourhood amenities: Beyond the Norm?

Journal:	*International Journal of Housing Markets and Analysis*
Manuscript ID	IJHMA-04-2017-0043.R1
Manuscript Type:	Research Paper
Keywords:	Housing markets, quantile regression, hedonic pricing model, house prices, externalities, neighbourhood amenities

Tables and Figures

Table 1 Variable Descriptives

Variable	Description	Type
Price	Sale Price in pounds sterling (£)	C
In Price	Natural logarithm of transaction Price	C
Area	Size of the property in m^2	C
Type	Type of property (Transformed to binary e.g. 1 if TER; 0 otherwise)	B
Class	Public or privately constructed (Transformed to binary e.g. 1 if PUB; 0 otherwise)	B
Bedrooms	Number of bedrooms (Transformed to binary e.g. 1 if 1BED; 0 otherwise)	B
Heating Type	Type of heating (Transformed to binary e.g. 1 if Gas; 0 otherwise)	B
Age	Age of the property (Transformed to binary e.g. 1 if PRE1919 ; 0 otherwise)	B
Garage	Transformed to binary e.g. 1 if GAR; 0 otherwise)	B
Time	Period of sale (Transformed to binary e,g, 1 if Q12014; 0 Otherwise)	B
Ward Location	Ward in which the property is located (Transformed to binary e.g. 1 if Ward1; 0 otherwise)	B
Multiple Deprivation	Level of multiple deprivation (deciles) (OA Level)	B
Crime Level	The number of recorded crime incidents (% per thousand) (Ward Level)	C
Unemployment	Unemployment rate (%) (Ward level)	C
CBD Distance	Distance to CBD [edge of CBD perimeter] (in bands) (metres)	B
Distance to Rail Halt	Distance to nearest rail halt (in bands) (metres)	B
Distance to Bus Stop	Distance to nearest bus stop (in bands) (metres)	B
Distance to Primary School	Distance to nearest primary school (in bands) (metres)	B
Distance to Secondary School	Distance to nearest secondary school (in bands) (metres)	B
Distance to GP	Distance to nearest GP Surgery (in bands) (metres)	B
Distance to Dentist	Distance to nearest Dentist (in bands) (metres)	B
Distance to Chemist	Distance to nearest Chemist (in bands) (metres)	B
Distance to Shopping centre	Distance to nearest Shopping Centre (in bands) (metres)	B
Distance to Open Space	Distance to nearest Area of public open space (in bands) (metres)	B

Notes: C – continuous; B – binary; OA – output area

Table 2 OLS and Quantile regression coefficient estimates

Parameter	OLS model		Quantile model													
			5th		10th		25th		50th		75th		90th		95th	
	β	*t*-stat	*β*	*t*-stat	*β*	*t*-stat	*β*	*t*-stat	*β*	*t*-stat	*β*	*t*-stat	*β*	*t*-stat	*β*	*t*-stat
(Constant)	10.887	311.31**	10.16	187.78*	10.321	269.1*	10.464	420.66*	10.594	468.59*	10.631	401.83*	10.726	509.6*	10.747	396.21*
Size	0.007	48.60**	0.007	17.48*	0.007	36.97*	0.007	38.40*	0.007	59.49*	0.007	41.987*	0.0078	54.55*	0.008	48.88*
Apartment	0.216	14.71**	0.232	6.67*	0.221	9.13*	0.296	16.33*	0.277	19.41*	0.324	20.69*	0.327	22.15*	0.311	20.86*
Detached	0.324	21.72**	0.280	7.49*	0.248	13.07*	0.238	14.78*	0.259	16.48*	0.272	13.07*	0.301	17.05*	0.363	12.35*
Semi-detached	0.146	15.85**	0.089	5.03*	0.063	5.51*	0.077	8.16*	0.101	10.23*	0.127	15.597*	0.117	14.18*	0.1186	12.34*
Social Built	-0.13	-10.79**	-0.140	-6.40*	-0.155	-9.54*	-0.159	-9.16*	-0.112	-6.88*	-0.096	-5.078*	-0.05	-4.39*	-0.037	-2.28**
No-Garage	-0.018	-2.45*	-0.004	-0.22	-0.009	-0.72	-0.021	-2.50*	-0.024	-3.01*	0.002	0.258	0	0	0.0035	0.37
Electric heating	-0.016	-1.25	-0.063	-2.74*	-0.067	-3.72*	-0.032	-2.60*	0.001	0.090	-0.029	-2.963*	-0.006	-0.184	-0.013	-1.05
Gas heating	-0.011	-1.48	-0.019	-1.368	-0.016	-1.64	-0.003	-0.351	-0.001	-0.141	-0.008	-1.25	-0.012	-1.528	-0.0008	-0.08
Solid heating	0.008	0.02	-0.001	-0.036	0.004	0.24	-0.008	-0.857	-0.004	-0.344	0.009	0.908	0.0064	0.843	0.0116	1.283
Pre-1919	-0.058	-4.31**	-0.017	-0.516	-0.074	-3.34*	-0.052	-3.774*	-0.041	-3.092*	-0.027	-1.97**	-0.041	-3.554*	-0.033	-2.291**
Post-1980	0.075	4.70**	0.196	6.075*	0.126	5.16*	0.099	7.145*	0.0855	4.270*	0.080	4.387*	0.0721	6.135*	0.0548	2.945*
Inter-war	0.002	0.18	0.011	0.416	-0.048	-2.48**	-0.035	-3.210*	-0.034	-3.404*	-0.030	-2.624*	-0.042	-4.497*	-0.0403	-3.344*
Early modern	0.02	1.53	0.112	3.582*	0.066	3.04*	0.067	5.158*	0.053	3.701*	0.0761	4.268*	0.0520	4.457*	0.0611	3.483*
Rail<200	-0.054	-1.91	0.092	0.989	0.064	2.51*	0.101	4.160*	0.1468	4.196*	0.1456	3.950*	0.1302	4.223*	0.1288	3.611*
Rail<400	-0.011	-0.47	0.001	0.022	0.087	2.69*	0.107	6.447*	0.1369	5.525*	0.1488	7.179*	0.1449	8.933*	0.1718	2.531*
Rail<600	-0.002	-0.11	0.164	4.407*	0.123	7.61*	0.125	7.967*	0.1154	10.09*	0.1016	5.628*	0.1098	7.246*	0.1631	13.480*
Rail<800	-0.013	-0.75	0.082	3.173*	0.058	2.50**	0.091	4.051*	0.1043	7.230*	0.1301	13.081*	0.1364	10.720*	0.1433	7.753*
Rail<1000	0.018	1.26	0.101	4.366*	0.103	5.206	0.084	4.813*	0.1044	8.451*	0.1117	7.996*	0.1306	14.211*	0.1321	7.097*
Bus stop<200	-0.006	-0.77	-0.033	-1.67**	-0.026	-2.33*	-0.041	-4.65*	-0.026	-3.45*	-0.002	-0.236	0.012	1.398	0.015	1.72
Bus stop<400	-0.014	-1.64	-0.036	-1.755*	0.004	0.262	-0.012	-1.243	-0.011	-1.145	-0.018	-2.15**	-0.015	-1.748	-0.0250	-2.985*
Sec school<200	0.061	2.89**	0.249	5.737*	0.160	5.101*	0.104	4.901*	0.1080	4.457*	0.0526	3.882*	0.0519	2.398*	0.0496	1.692
Sec school<400	0.045	3.31**	0.159	4.810*	0.124	7.022*	0.077	5.991*	0.0518	3.506*	0.0470	3.073*	0.0671	4.301*	0.0581	4.342*

Sec school<600	0.012	1.07	0.065	2.9503*	0.049	2.912*	0.013	1.123	-0.002	-0.175	-0.003	-0.238	0.0237	2.393*	0.0156	1.246
Sec school<800	-0.013	-1.42	0.026	1.087	0.011	0.893	-0.010	-0.946	0.0181	1.873	0.0071	0.66	0.0371	4.016*	0.0309	3.447*
Pri school<200	-0.02	-2.11*	-0.047	-2.442**	-0.036	-2.40**	-0.042	-3.787*	-0.0444	-4.1712*	-0.0434	-4.895*	-0.051	-5.732*	-0.0468	-4.282*
Pri school<600	0.008	0.98	0.011	0.536	0.006	0.557	0.011	1.183	0.0137	1.538	0.0060	0.658	0.0252	3.278*	0.0132	1.445
Pri school<800	0.028	2.17*	0.012	0.486	0.006	0.414	0.002	0.191	-0.004	-0.287	-0.004	-0.294	0.031	2.719*	0.020	1.696
Pri school<1000	0.049	2.33*	0.015	0.408	0.033	1.097	0.038	1.607	0.0835	4.2797*	0.0490	1.974**	0.0329	1.49	0.0049	0.131
Open<200	-0.001	-0.04	-0.101	-2.27**	-0.085	-1.202	-0.060	-1.260	-0.0043	-0.160	0.0050	0.331	0.0079	0.433	0.0321	1.048
Open<400	0.003	0.27	-0.078	-3.672*	-0.087	-5.699*	-0.035	-2.494*	-0.0363	-2.728*	-0.0494	-2.976*	-0.039	-3.029*	-0.0278	-1.996**
Open<600	-0.016	-1.70	-0.065	-2.500**	-0.074	-5.296*	-0.041	-2.929*	-0.0194	-1.746	-0.0254	-2.741*	-0.028	-3.524*	-0.0111	-1.145
Open<800	0.012	1.48	0.043	2.477**	0.023	2.08**	0.003	0.346	-0.013	-1.514	-0.0078	-0.99	-0.008	-1.017	0.0003	0.038
Open<1000	0.211	8.87**	0.033	0.489	0.044	1.035	0.074	2.765*	0.0215	1.235	0.0253	0.749	0.1027	1.87	0.1753	3.391*
Adjusted R^2	0.818															
F-Statistic/ AIC	143.4*		2108		1260.9		1260.9		-660.96		-507.87		283.81		944.85	
n	3,780		3,780		3,780		3,780		3,780		3,780		3,780		3,780	

Dependent variable: Ln Sale Price; β = unstandardised beta; **Denotes significant at the 99% level; *95% level.
Model presented in its most parsimonious format for space requirement. Excludes: Wards (location) and time.

Table 3 Summary of variables which depart from the OLS

Variable	OLS *β*	Quantile *β*	Δ coefficient	Δ in *Sig.*	Trend in pricing (increase/decrease)
Apartments	.216	75^{th} = .324	+.108	Yes	Positive toward (HQs)
		90^{th} = .327	+ .111		
Detached	.324	10^{th} = .248	-.076	No	Negative toward (LQs)
		90^{th} = .363	+.039		Positive toward (HQs)
Social built	-.130	95^{th} =-.037	-.093	No	Negative toward (HQs)
		90^{th} = -.050	-.080		
Post-1980	.075	5^{th} = .196	+.121	No	Positive toward (LQs)
		10^{th} = .126	+.051		
Inter-war	.002	10^{th} = -.048	-.048	Yes	Negative toward (All Qs except 5^{th})
		95^{th} = -.040	-.040		
Early modern	.02	5^{th} = .112	+.092	Yes	Positive toward (All Qs)
Rail <200	-0.054	50^{th} = .146	+.200	Yes	Positive toward (All Qs)
Rail <400	-0.011	95^{th} = .178	+.189	Yes	Positive toward (All Qs)
Rail <600	-0.002	5^{th} = .164	+.162	Yes	Positive toward (All Qs)
		95^{th} = .163	+.161		
Rail <800	-0.013	95^{th} = .143	+.142	Yes	Positive toward (All Qs)
Rail <1000	0.018	5^{th} =.101	+.100	Yes	Positive toward (All Qs)
		95^{th} =.132	+.131		
Bus Stops<200	-0.006	25^{th} =.041	-.040	Yes (LQ's)	Negative toward (All Q's except 90^{th};95^{th})
Bus Stops<400	-0.014	5^{th} = -.036	-,022	Yes (LQs; HQs)	Negative toward (All Q's except 10^{th})
		95^{th} = -.025	-.011		
Sec School <200	0.061	5^{th} = .249	+.18.8	No	Positive toward (LQs)
Sec School <400	0.045	5^{th} = .159	+.114	No	Positive toward (LQs)
Sec School <600	0.012	5^{th} = .065	+.053	Yes	Positive toward (LQs)
Sec School <800	-0.013	90^{th} =.037	+.050	Yes	Positive toward (HQs)
		95^{th} = .031	+.044		
Open space <200	-0.001	5^{th} = .101	+.101	Yes	Positive 5^{th} Q only
Open space <400	0.003	5^{th} = -.078	-.078	Yes	Negative toward (LQs)
		10^{th} = -.087	-.087		
Open space <600	-0.016	5^{th} = -.065	+.049	Yes	Positive toward (LQs)
		10^{th} = -.074	+068		
Open space <800	0.012	5^{th} = .043	+.031	Yes (LQs)	Positive toward (5^{th}; 10^{th} Qs)
Open space <1000	0.211	95^{th}= .173	+.152	No	Positive (95^{th} Q only)

NB: The most extreme deviations are presented. LQs depicts Lower Quartiles; HQs depicts Higher Quartiles.

Figure 1 OLS and Quantile estimates for property type

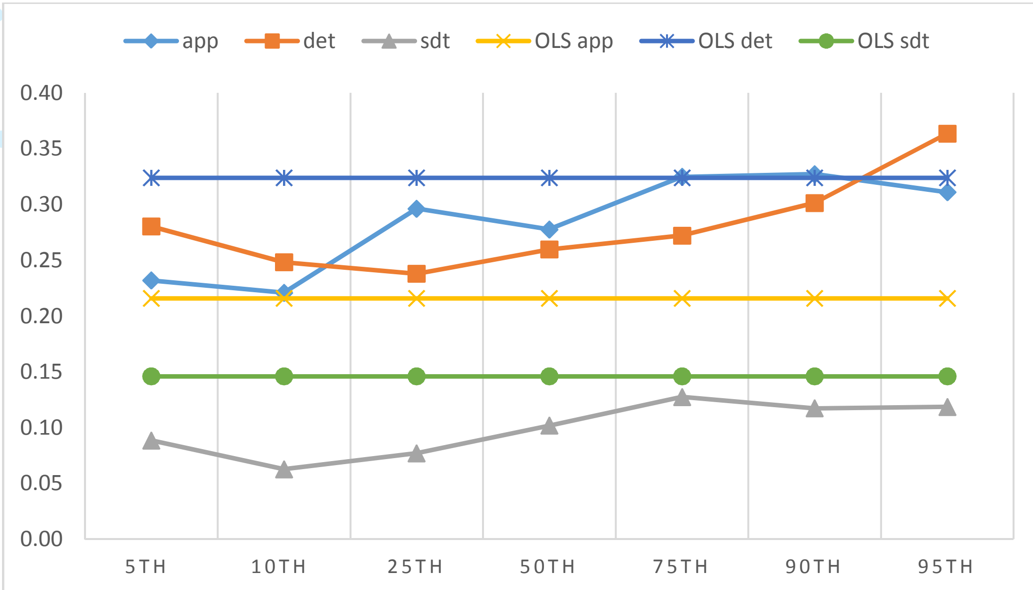


Figure 2 OLS and Quantile estimates for property Age

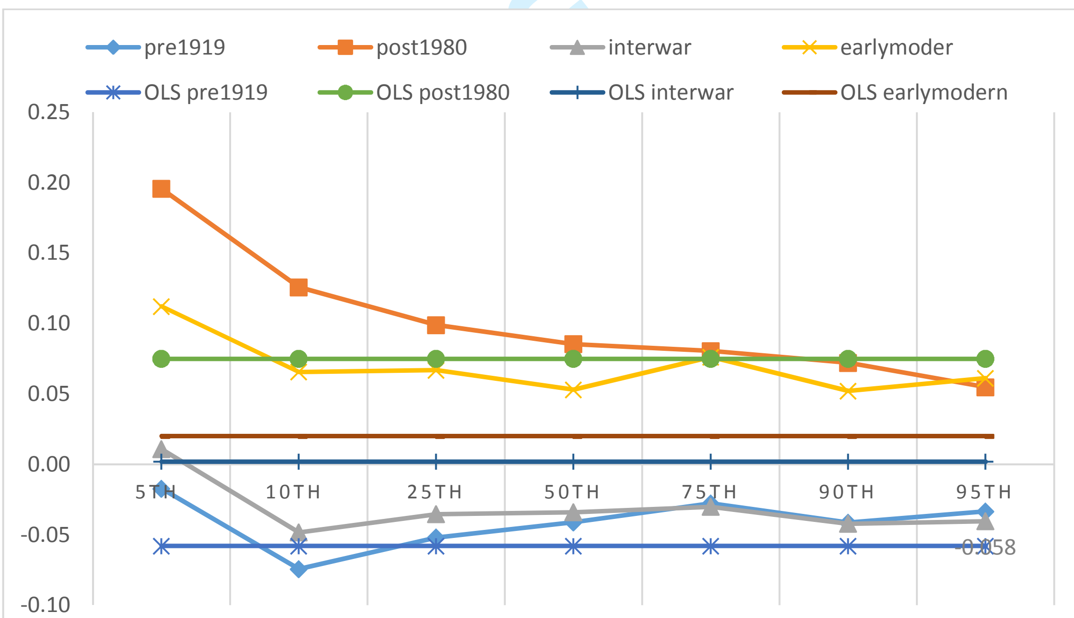


Figure 3 Distance to Rail Halts OLS and Quantile coefficients

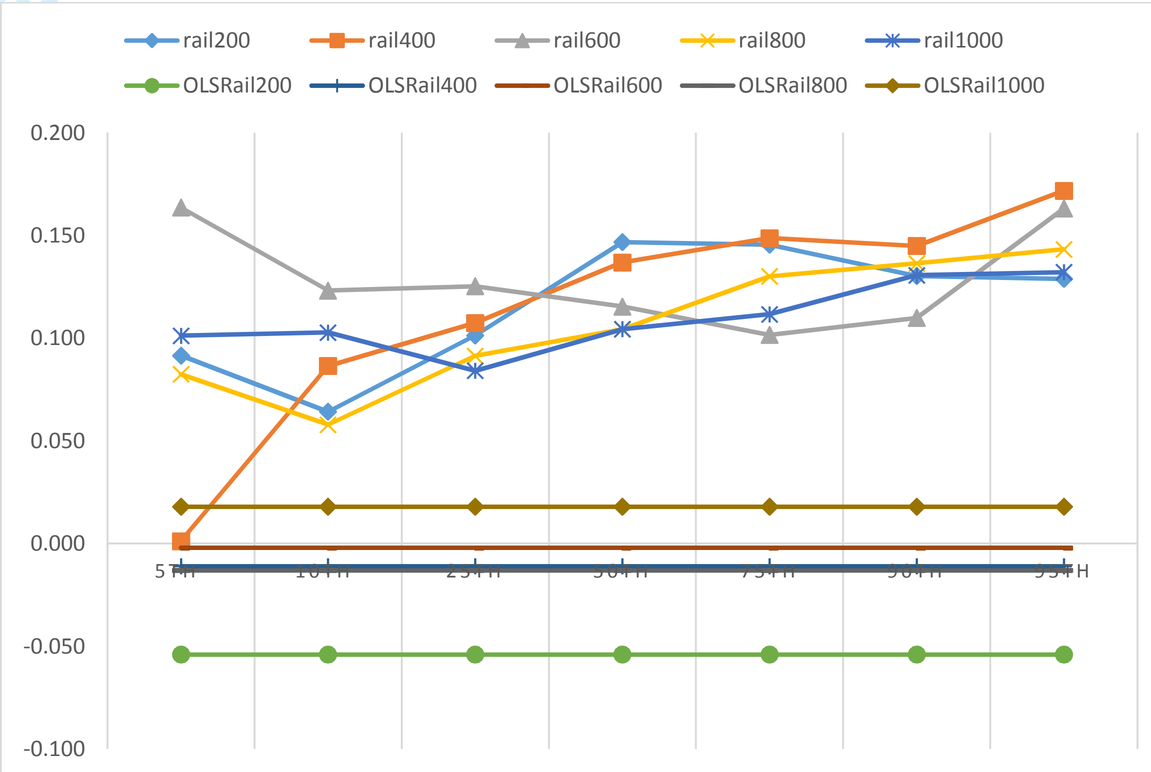


Figure 4 Distance to Secondary schools OLS and Quantile coefficients

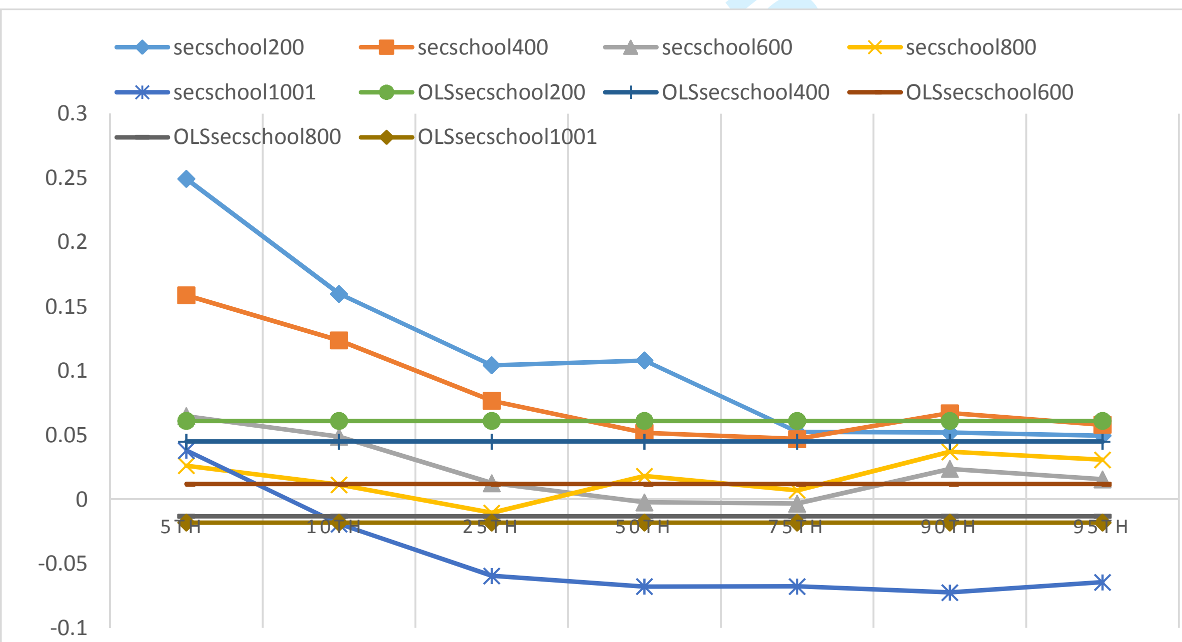


Figure 5 Distance to Primary schools OLS and Quantile coefficients

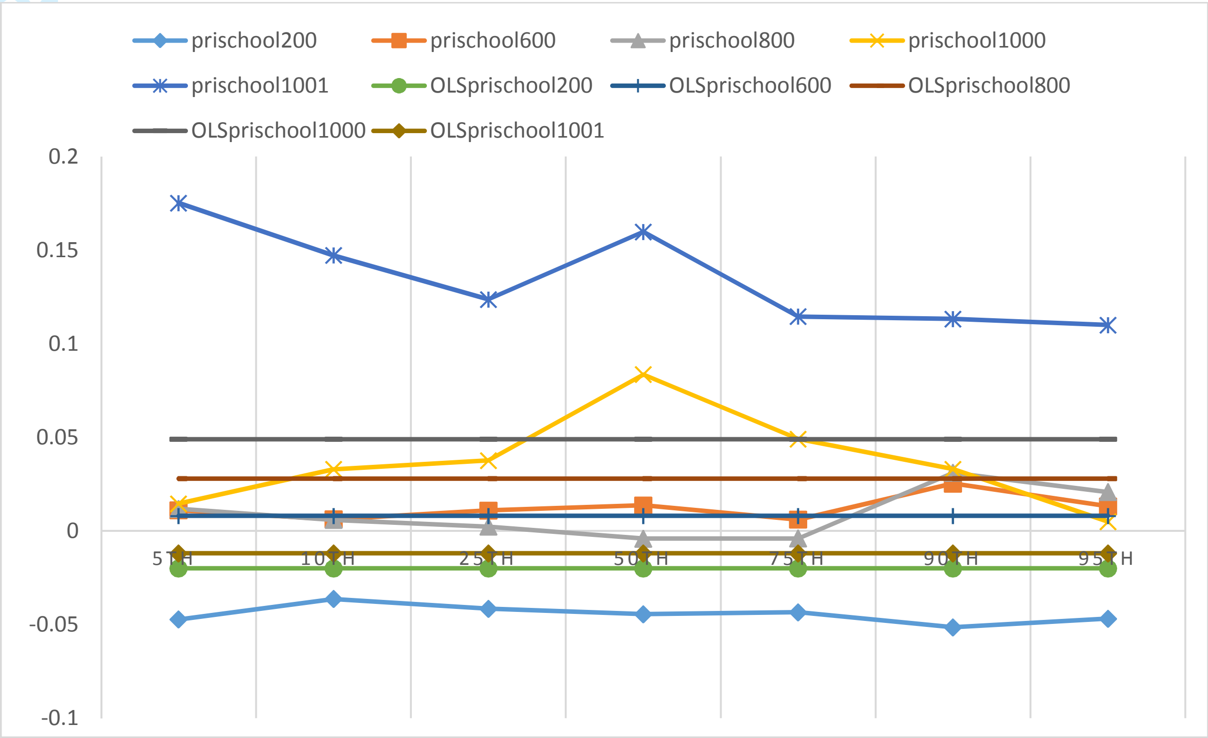
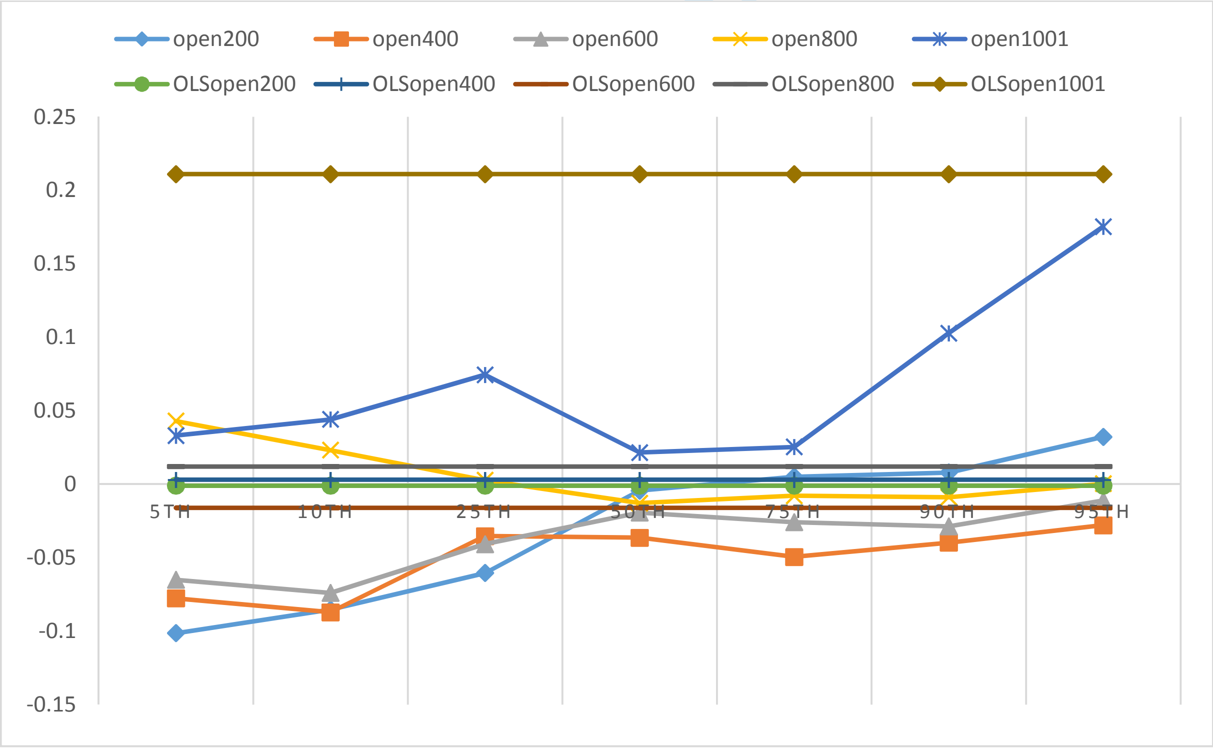


Figure 6 Distance to Public Open Space OLS and Quantile coefficients



House Prices and Neighbourhood amenities: Beyond the Norm?

ABSTRACT

Purpose: Understanding the key locational and neighbourhood determinants and their accessibility is a topic of great interest to policy makers, planners and property valuers. In Northern Ireland, the high level of market segregation means it is problematic to understand the nature of the relationship between house prices and the accessibility to services and prominent neighbourhood landmarks and amenities. Therefore, this paper attempts to quantify and measure the (dis)amenity effects on house pricing levels within particular geographic housing sub-markets.

Design: Most hedonic models are estimated using regression techniques which produce one coefficient for the entirety of the pricing distribution, culminating in a single marginal implicit price. This paper employs a quantile regression approach which provides a 'more complete' depiction of the marginal impacts for different quantiles of the price distribution using sales data obtained from 3,780 house sales transactions within the Belfast Housing market over 2014.

Findings: The findings emerging from this research demonstrate that housing and market characteristics are valued differently across the quantile values and that conditional quantiles are asymmetrical. Pertinently, the findings demonstrate that OLS coefficient estimates have a tendency to over or under specify the marginal mean conditional pricing effects due to their inability to adequately capture and comprehend the complex spatial relationships which exist across the pricing distribution.

Originality: Numerous studies have used OLS regression to measure the impact of key housing market externalities on house prices, providing a single estimate. This paper uses a quantile regression approach to examine the impact of local amenities on house prices across the house price distribution.

KEY WORDS: housing markets, quantile regression, hedonic pricing model, house prices.

Introduction

Housing can be considered as a bundle of utility-bearing characteristics. As such; the implicit price of property attributes can be revealed from the observed prices of differentiated products and the quantities of characteristics associated with them. These characteristics are often decomposed into vector implicit structural attributes, neighbourhood and environmental traits and accessibility estimates (Kim *et al*., 2015). This approach observes the unbundling of the housing product to assess the (implicit) value that individuals are revealing by their (explicit) choices in the housing market (Sheppard, 1999). Price modelling in housing markets traditionally applies hedonic ordinary least squares (OLS) regression modelling originally pioneered by Lancaster (1966) and Rosen (1974). However, Koeneker and Hallock (2001) suggest that simple OLS assumes a constant marginal impact across the entire distribution of the dependent variable – such assumption is not always prevalent in housing markets. Indeed, research conducted by Sirmans et al. (2005) demonstrates high variability in magnitude and direction of coefficient estimates between housing characteristics and house prices. This heterogeneity and diverseness within results, whilst illuminating the idiosyncratic nature of 'specific' markets and behaviour/preference choices (Malpezzi, 2003), also points towards 'quantile effects' which occur when housing characteristics are valued differently across the conditional distribution of house prices (Liao and Wang, 2012; Zhang and Leonard, 2014). Essentially, pricing effect varies across the price spectrum.

To address this, a viable approach for understanding the price relationship is the application of quantile regression. This method dissects the pricing into quantiles to explore the effect of the explanatory variables across the pricing distribution, by estimating the changes in a specific quantile. This permits a more comprehensive understanding of the effect of explanatory variables on house prices as well as modeling the difference in the level of the effect. At the same time it reflects changes in the magnitude of the coefficients (Kim *et al.*, 2015). As highlighted by Newsome and Zietz (1992), this eliminates the biased estimation issues when applying the OLS estimation to house price sub-samples and is particularly valuable for the examination of segmented markets, as it reduces statistical issues related to truncated data based on the mean value (Heckman, 1979).

House price analysis within the Northern Ireland, and specifically, the Belfast housing market is limited, with existing studies tending to employ the standardised hedonic framework. Whilst the results of these extant studies have demonstrated robust findings as to the marginal effects on house prices, arguably they have failed to account for the variability across the price spectrum and the associated impacts of housing choice. This is an important issue pertinent to the Belfast housing market, as it is unique (asymmetrical) in its market characteristics which has a tendancy to distort normal market behaviour and activity. Belfast has emerged unevenly from conflict and remains a bifurcated city (Murtagh and Keaveney, 2006). Whilst the last decade observed a stabilisation in ethno-religious segregation due to peace, political stability, growth in the macro economy, housing market and in business confidence; Belfast's post-conflict renaissance remains somewhat questionable as issues such as multiple deprivation (the spatial distribution of deprivation or disadvantage), ethno-religious segregation and a sense of residential fatalism (unalterable housing choices) remain. Indeed, Murtagh (2011) observes that new mixed housing spaces have developed in the high-value end of the housing market, manifesting in "class restructuring" and socio-spatial segregation, or clustering. McCord et al. (2013) highlight that this has changed the topographical composition across the housing market. Indeed, the existing bifurcated market impacts upon the pricing structure across the market and importantly upon access to services and amenities. The result of these processes has manifested in a complex mosaic of price patterns distinguished by enclaves of gentrification and deprivation as a result of extant barriers such as peace walls which scar the Belfast hosing market landscape. The continued access to contested space and the associated policy remedies has resulted in market based (both economic and social) implications which have undoubtedly further impacted upon access to services and neighbourhood amenities.

In response to these issues, this paper empirically estimates the effect of housing characteristics across the Belfast housing market, specifically examining key neighbourhood amenities, in order to determine whether any differences exist in the hedonic effects between the quantile house price levels. This provides further understanding of the effects of specific property and locational features when estimating pricing within the Belfast housing market and is important for illustrating the potential variability in attribute and locational effect across the price spectrum elsewhere.

The paper proceeds as follows. Section 2 reviews the relevant literature related to house prices and the role of externalities within housing markets, detailing the considered value proposition of quantile hedonic analysis relative to more conventional OLS modelling techniques. This is followed by the data and methodology in section 3, with the results presented and discussed in Section 4. Finally, some conclusions are offered in Section 5.

Literature Review

In the context of housing literature, amenities and environment effects are key considerations and hedonic methods with spatial analyses have gained popularity to provide estimates of the proximity "effect" of a variety of positive and negative environment-specific externalities on property prices (Des Rosiers *et al.*, 1999; Irwin, 2002; McConnell and Walls, 2005). Indeed, over the past four decades, a plethora of studies have reported significant positive and negative effects on house price from a variety of proximate locational externalities (Quang and Grudnitski, 1994; Kauko, 2003) inferring that the value of a specified (dis)amenity is, at least, partially captured in the price of residential properties proximate to it (Crompton, 2001). This includes an extensive volume of research devoted to estimating amenity values for land use diversity and landscape structure (Patterson and Boyle, 2002; Des Rosiers *et al.*, 2002). A large and growing literature estimates the effects of neighbourhood open space on residential property values (Bolitzer and Netusil, 2000; Tyrväinen and Miettinen, 2000; Lutzenhiser and Netusil, 2001, Smith *et al.*, 2002). There is a burgeoning body of work relating to the property value impacts of home location proximate to neighbourhood style and distance and accessibility to amenities (Hendon, 1972; Espey and Owusu-Edusei, 2001; Morancho, 2003; Song and Knaap 2004; Van den Berg and Ter Heijne, 2005; Jorgensen *et al.*, 2007; Kong *et al.,* 2007; Zhang *et al.,*2012; Brunauer et al., 2013; Dziauddin et al., 2013; Liao and Chen; 2013; Reed, 2013; Dubé et al., 2014).

Nonetheless, this extensive volume of existing research show differing and mixed pricing effects of proximity to neighbourhood amenities and house prices, and perhaps more pertinently, this research has tended to consider the mean effects only - assuming that, on a percentage basis, conditional house prices are all equally affected by neighbourhood characteristics and amenities. Indeed, studies such as Bayer *et al*. (2004), who examined equilibrium residential sorting, provide empirical evidence that confirms these differences with their estimates precisely characterising these preferences. Their study found that marginal willingness-to-pay for desirable housing characteristics and location attributes, including neighbourhood socio-demographic compositions, accessibility to workplace and proximity to amenities, increases with income.

In this regard, literature on house prices had not examined this diffuse dimension until recent applications of quantile regression (Mueller and Loomis, 2014). Quantile regression is particularly useful when examining segmented markets (such as what occurs in most urban residential housing markets). The full characterisation of the conditional distribution, rather than the conditional mean, of house prices is examined in several studies (Gyourko and Tracy, 1999; Coulson and Mcmillen, 2007; McMillen, 2008; Zietz *et al*., 2008; Mak *et al*., 2010; Ebru and Eban, 2011). Indeed, the seminal investigation by Gyourko and Tracy (1999) demonstrated that quantile analysis estimated quality improvements in high-end housing much higher than the original OLS specification. Coulson and McMillen (2007) and

McMillen (2008), who construct quantile house price indexes and reflect on house price appreciation, identify significant variations in the values of physical attributes across conditional quantiles. In a similar vein, other studies employing quantile regression find strong evidence that marginal implicit prices vary across the conditional distribution of house prices. Liao and Xizhu (2012) present evidence of 'substantial variation' of the implicit prices of housing characteristics within a quantile regression framework in the Chinese context. Other studies conducted by Mak *et al.* (2010), and Ebru and Eban (2011) employed quantile regression techniques to analyse Hong Kong and Istanbul real estate prices respectively, revealing that housing attributes were valued differently across the conditional price distribution. Significantly, the findings of Mak *et al.* (2010) showed that quantile effects exist even for single condominiums. Zietz *et al*. (2008) applying a novel spatial quantile regression for Orem-Provo, Utah, discovered that housing attributes are valued quite differently across the conditional price distribution, however, they observe negligible spatial dependence and conclude that quantile effects are of greater importance. In a different context, a study conducted by Xuming and Yicheng (2009) applied the quantile regression methodology to examine the accuracy of mass appraisal for the purpose of real estate taxation and mortgages. Their findings illustrated that property characteristics impact differently to real estate prices within different value ranges.

The corpus of the existing research presents persuasive evidence that the relationship between house prices and neighbourhood amenities and characteristics is complex and not all forms of neighbourhood externalities are valued equally by households. This is enshrined in the seminal hedonic theoretical construct as furnished by Rosen (1974) who proposed that identical houses in similar neighbourhoods will have different prices if the houses have different levels of environmental amenity or disamenity. Ultimately this implies that potential buyers may be willing-to-pay more (less) for (dis) amenity proximity preference thus resulting in house price differentials between houses with varying levels of environmental (dis)amenity is buyers' marginal willingness-to-pay.

The value of going beyond the conditional mean model has been demonstrated in rapidly expanding literatures in econometrics, social sciences, and more latterly in property studies. Quantile regression has arguably emerged as a useful supplement to ordinary mean-based regression. As existing literature findings illustrate, the upper or lower quantiles of the response variable depend on the covariates very differently from the mean. Therefore, quantile regression can provide a more complete description of functional changes than focusing solely on the mean. This makes very minimal assumptions on the form of error distribution and thus is able to accommodate non-normal errors, which are common in many applications (Koenker, 2005; Reich et al., 2010). Despite this emerging corpus of literature, some recent studies have illustrated challenges pertaining to the quantile approach. Reich et al. (2010) note that although theory for quantile regression is well versed, the development of convenient inference procedures has been challenging, as the asymptotic covariance matrix of quantile estimates involves the unknown error density function, which cannot be estimated reliably.

Moreover, Beyerlein (2014) indicates that the quantile regression approach is based on 'samples' meaning that assessing the 'quantiles' or percentiles can be difficult. Nonetheless the author does indicate that this problem may be solved by assessing the percentage of observations at or below the respective threshold and then modeling the associated quantile. This is also acknowledged by Reich et al. (2010) who highlight that inference for quantile models is challenging, particularly for clustered or censored data, as limited options exist for inferential analysis. This has been subject to various research studies amongst others (Jung, 1996; Lipsitz, 1997; Yin and Cai, 2005 and Wang and Fygenson, 2009).

Another challenge corresponds to the wider applicability of 'intuitive interpretation' (Koenker, 2005). The interpretation of a single measure obtained from linear regression appears more straightforward than the interpretation of a number of quantile regression coefficients, which may not combine to form a simple picture. As quantile regression coefficients quantify how much a specific quantile of the outcome distribution is shifted by a one-unit increase in the predictor variable, this interpretation is consonant to that of linear regression. Indeed, the only tangible difference is that of an average difference for standard linear regression - whereas there is no appropriate terms in common language to easily describe results from quantile regression (Reich et al., 2010). Despite this lack of clarity (in some instances), as existing studies have tended to highlight, the pattern of regression coefficients over the whole range of quantiles reveal the true nature of the underlying associations. Whilst simplicity of interpretation is an important criterion for the choice of a statistical approach, the quantile regression method is not considerably inferior to linear regression. In contrast, it offers much more information and is less sensitive with respect to the distribution of the outcome variable (Beyerlein, 2014).

Data and Methodological framework

Data

The sales information is drawn from the Belfast housing market comprising 3,780 sales transacted during 2014. The initial dataset comprising 3,853 observations was examined for outliers and other data anomalies and subjected to statistical procedures[1] for outlier removal (resulting in 73 cases being removed). In addition, missing observations were purged along with those incorrect as a consequence of erroneous data entry. Where appropriate, variables were transformed into a binary state as illustrated in **Table 1**. To capture accessibility, services and important amenities, distance calculations were ascertained using *X, Y* coordinates for each sales observation. Census tract data was sourced from the Northern Ireland Neighbourhood Information Statistics (NINIS) and Northern Ireland Statistical Research Agency (NISRA). At the census geography, where feasible, Output Areas (OAs)[2] [the lowest level geographic information], were utilised to account for and provide specific demographic, socio-economic characteristics (for example; level of employment, population demographics and the Multiple Deprivation Measure (MDM))[3]. Where appropriate, the Euclidian distance measures were transformed into distance band dummy variables. This was a necessary step in order to band each respective property attribute and distance to nearest market amenity and service. This step also served to ensure sampling adequacy for the hedonic modelling stage. The variables utilised in the statistical analysis are evidenced in **Table 1**.

<<<Insert Table 1 Variable Descriptives>>>

Hedonic modelling

Hedonic modelling is the traditional technique applied within property analysis to ascertain the marginal effects of property attributes to capture the relationship between house prices and housing/spatial attributes. Typically, as identified in the seminal writings of Rosen (1974) the

---

[1] This research employed Cook's distance procedure to remove problematic outlier cases using the criteria formula: $4/(n - k - 1)$, where n is the number of cases in the analysis and k is the number of independent variables.

[2] OA's are computer-generated and intended to be of uniform population size, take account of postcode and ward B boundaries and to be as socially homogeneous as possible. The 5,022 Northern Ireland OAs contain an average of 336 persons and 125 households. The minimum threshold for publication of census data was 100 persons and 40 households.

[3] The Multiple Deprivation Measure provides information on seven types or 'domains' of deprivation and an overall multiple deprivation measure comprising a weighted combination of the seven domains presented at the Output Area and Super Output Area geography. The MDM was further dissected into deciles and transformed into binary state

basic form of the house price model is the functional relationship between the price P of a heterogeneous good i and its quality characteristics represented by a vector $\boldsymbol{x}_i$:

$$P_i = f(\boldsymbol{x}_i;\ \boldsymbol{\beta}) + u_i \tag{1}$$

Where P_i is a property with a price P, $\boldsymbol{x}_i$ *is* the structural attributes of size and quality, and also attributes of the neighbourhood in which the property is located (indicators of the adjacent environment and accessibility), $\boldsymbol{\beta}$ relates to the vector of coefficients which are estimated for the characteristics, with u_i representing the error term.

The hedonic approach is however open to critique as the price function is an envelope function signifying that there is no 'exact' theoretical guidance for its specification which can give rise to mis-specification challenges, particularly for any given sample data. In the absence of clear guidance, it is appropriate to test several functional forms such as the semi-logarithmic or logarithmic-logarithmic (multiplicative) hedonic equation in order to determine the optimal approach. In this regard, the semi-log hedonic specification can be applied where:

$$In(P_i) = \alpha + \sum_{j=1}^{J} \beta_j z_{ji} + e_i \tag{2}$$

where the natural log of the i^{th} house is a function of the J characteristics assumed to influence price, α and β the coefficients estimated, and e the normally distributed error term. When employing the semi-log specification, the functional form facilitates the evaluation of the percentage effect. As highlighted by Halvorsen and Palmquist (1980) for the semi-log model specification capturing the true percentage change of a dummy variable is:

$$g = 100[\exp([\alpha]) - 1] \tag{3}$$

Where; the relative effect on the dependent variable of the presence of the factor represented by the dummy variable bn.

In order to identify the influence of different factors on real estate value, this paper introduces a quantile regression model to analyse the factors. For assessment value functions, quantile regression makes it possible to statistically examine the extent to which housing characteristics are valued differently across the distribution of housing values. In line with Koenker and Hallock (2001) and Kim *et al.* (2015) methodologies, quantile regression is based on the minimization of weighted absolute deviations to estimate conditional quantile (percentile) functions (Koenker & Bassett, 1978), where the quantile hedonic specification generalizes the concept of unconditional quantile to a quantile of conditioned on one or more covariates. For the median (quantile=0.5), symmetric weights are used, and for all other quantiles asymmetric weights are employed[4]. In contrast, where classical OLS estimates conditional mean functions, quantile regression employs the full data set, a sample selection problem does not arise (Xuming and Yicheng, 2009), as this avoids the problem of truncation. Least squares minimizes the sum of the squared residuals, therefore, the symmetry of the piecewise linear absolute value function implies that the minimisation of the sum of absolute residuals must equate with the number of positive and negative residuals, ensuring the same observations above and below the median.[5]

Model Parsimony

Initial model inspection of the standardised residuals for both the linear and semi-log forms was undertaken to establish the relative 'goodness of fit' and account for any potential neglected nonlinearities within the OLS specification. Given the importance of the relationship between price and building size (floor size in m^2), this was initially inspected in order to establish whether any non-linearity exists for optimal model structure. As evidenced in **Appendix 1**, the log-Price and area relationship explains 39.3%, whereas the Log-Price and Log-Area explains 34.5%, illustrating that the Area (Size) variable requires no further transformation. Nonetheless, preliminary analysis highlighted issues pertaining to model structure given the inclusion of neighbourhood characteristics, which have a tendancy to demonstrate spatial autocorrelation. Whilst spatial autocorrelation within spatial econometric analysis remains a significant and emerging field of study, considerable debate still concerns which is the most apposite approach for addressing it and how the variation in the methods impact upon spatial dependence (For a full discussion see Koschinsky et al., 2012). Setting that aside, the model developed within the confines of this research does not employ a 'spatial econometric' model, rather, the OLS specification encapsulates locational (fixed spatial effects) dummies employing sub-markets (OA level using electoral market

[4] see endnotes for a full methodological overview
[5]See Endnotes for a full discussion

delineation) to control for the spatial component when testing the quantile regression approach. Therefore, the models developed compare the traditional global OLS with a Quantile OLS which both employ spatial dummies to permit robust comparison.

To address any issues pertaining to multicollinearity within the OLS and QR approach, a model selection procedure was employed to increase model robustness, stability and to handle detrimental variables. As discussed by deSmith *et al.* (2007), whilst the inclusion of additional estimators can enhance model performance, this can contrive and distil the explanatory relationships between parameters and culminate in an excessively complicated model structure which is often difficult to interpret (particularly when examining neighbourhood (spatial) characteristics). In this regard, this paper employs the most parsimonious model format, whilst maximising model performance. To select the optimal model structure, model development was tested using a regression procedure in order to classify any detrimental variables. Diagnostic analysis employing the Variance Inflation Factor (VIF) and Tolerance limits were also scrutinised to measure any influential variables (For full model see Appendix 1). This approach was further complimented using an information theoretic statistic, the Akaike Information Criterion (AIC). This statistic is premised on the maximum likelihood estimates of the model parameters where the probability of the observed data would be as large as possible. The estimates are based on maximum likelihood estimates of the model parameters which provide an approximate AIC value:

$$AIC = n + n\, In(2\pi) + \ nlog\left(\frac{RSS}{n}\right) + \ 2K \tag{6}$$

This multi-model inference procedure was applied to ensure the most appropriate explanatory variables were included in the final modelling phase[6] with the selection procedure filtered by the AIC. The model inference was conditioned on fixed explanatory variables containing all spatial and neighbourhood characteristics, with the predictor floating variables comprising the structural variables. This permitted the minimum AIC value and most parsimonious model for analysis[7] to be deployed. The initial iterative modelling results revealed that the

---

[6]According to Burham and Anderson (2002, 2004) if the value of δAIC is higher than 7 the model has a relatively poor fit relative to the best model, whereas a value less than 2 indicates that a model is equivalent to the minimum AIC model.

[7]The RSS is the sample residual sum of squares and K is the number of estimable parameters in the model including the intercept and the residual variance $\hat{\sigma}^2$. This balances error with model complexity (increasing K), with the optimal model comprising the minimum AIC score. This equation gives the small sample

most parsimonious model form excluded crime and unemployment neighbourhood variables – perhaps as they are already captured within the indicators which constitute the measure of Multiple Deprivation and a number of the neighbourhood convenience amenities, such as distance to the CBD, doctor surgeries, dental practices, pharmacists and shopping centres. Interestingly, the bedroom coefficients and distance to CBD displayed no statistical significant effects or additive value to the explainability within the model framework. Furthermore, the bedroom coefficients also exhibited severe levels of Variance Inflation[8], likely demonstrating a collinear relationship with property size (Appendix 1). As a consequence these structural and neighbourhood predictors were removed from further analysis.

Empirical Results and findings

The empirical analysis is conducted on the OLS regression and subsequent quantile regression employing seven quantiles across the house price distribution, as evidenced in **Table 2**.

<<<Insert Table 2 OLS and Quantile regression coefficient estimates>>>

Property (structural) attributes

In terms of comparison, the OLS and quantile coefficients show a general trend in terms of the estimates sign and statistical significance for the structural characteristics of the properties. Examination of the size (m^2) parameter within the OLS and quantile estimates shows that they are all statistically significant, with marginal effects only increasing above the 50th percentile of the price distribution - which incrementally increase as per each quantile (95th quantile; β = .008, p<.05). This suggests that size is valued differently across the quantiles and that conditional quantiles are not identical. Indeed, the results show this effect when considering the nature of the property type (**Figure 1**). The analysis exhibits OLS

approximation (AIC_C), that converges to standard AIC for large samples. The value of $\sigma 2$ is used as a proxy for the likelihood of the model given the data. The AIC values for the various models are transformed to ΔAIC, which is the difference between AIC of each model and the minimum AIC found for the set of models compared

[8] VIF signifies the magnitude of inflation within the standard errors associated with the beta weight. Various acceptable levels of VIF have been used in extant research (Pan and Jackson, 2008 = 4; Rogerson, 2001 =5; Hair and Anderson, 1995 = 10).

coefficients to generally over or under specify the marginal mean conditional pricing effects. Scrutiny of the type of property reveals a number of (relatively) high disparate pricing effects. For apartments, estimates shows the OLS coefficient effect of 0.216 (t = 14.717, p<.01) is more relative to the coefficient estimates for both the 5th and 10th quantiles (β = .232; β = .221), whereas above the 25th quantile the OLS underestimates the positive pricing effect by circa 10%. Alternatively, for detached properties the mean conditional OLS coefficient generally over specifies the effect when comparing against the quantiles. Below the 90th quantile estimate, the results show a high variability of around 7-8% (at the 10th and 25th quantile) demonstrating that the OLS mean conditional estimate is tending to over value and is more reflective of the higher priced properties. This is a similar picture for the semi-detached properties as evidence in **Figure 1**.

<<< Insert Figure 1 OLS and Quantile estimates for property type>>>

Interestingly, the construction of publically built housing (social built) shows a different relationship illustrating the OLS estimate to be relatively concomitant up to the 50th quantile which diminishes significantly up the 95th quantile. Significantly, this shows a marginal decrease in the level of the pricing effect the higher up the quantile distribution, and that higher valued socially built housing has a diminished effect than lower valued socially constructed housing (**Table 2**). Scrutiny of the garage coefficient (no garage) also reveals that the OLS, and quantile coefficients - up to the 50th quantile, bear the same sign with marginal fluctuation in coefficient values. Pertinently, above the 50th quantile the estimates turn positive and are not statistically significant. This infers that the effect or value of having no garage is only a contributory factor at the lower and mean value range of housing in the sample.

Analysis of property age reveals a mixed picture across the sample. Pre-1919 built properties demonstrate relatively marginal movement across the pricing distribution. This is undoubtedly due to pre-1919 housing generally being homogenous housing stock (characteristically small terrace housing or large Edwardian houses). The findings do however reveal some marked differences across the distributional quantile values in terms of effect and statistical significance across the age profile of housing. Post-1980s properties reveal that across the quantiles there is a higher pricing effect in comparison to the OLS coefficient, which diminishes the further up the quantiles towards the higher priced properties. The differential is relatively large (5th Quantile: β = .196, p<.05; OLS: β = .075, p<.00). For inter-war[9] period properties, the OLS coefficient is statistically insignificant (β =.002: t =.181, p>.05). However there is a more complex relationship which emerges when analysing the quantiles (**Table 2**). At the 5th Quantile level of the pricing distribution β = .011, however is statistically insignificant. From the 10th quantile to the 95th quantile the findings show a statistically significant negative pricing effects of circa 3% to 4% (**Figure 2**), revealing a completely different finding to the conditional mean OLS coefficient. A similar depiction is observed when investigating the early modern property age coefficient. The OLS variable displays a statistically insignificant β of .02, whereas the quantile analysis shows a higher value at the 5th quantile (β = .112, p<.05) which also marginally varies between .052 and .076 across the remaining quantiles, which are all statistically significant at the 95% level. The results therefore show that when analysing the pricing distribution, the OLS coefficient appears to not capture a 'truer' depiction of the age characteristics of the properties, and indeed clearly shows that these effects are complex and idiosyncratic across each type and price level, undoubtedly due to the heterogeneity between housing price, size, age and type.

<<<Insert Figure 2 OLS and Quantile estimates for property Age>>>

Public Transportation

Turning to the external neighbourhood amenities and services, proximity to public transportation shows a very disparate pricing effect across each of the coefficients price distribution. Proximity to rail halts/stations reveals a negative OLS estimates across all the distance bands, with the exception of >1000 metres which is slightly positive. All OLS estimates are statistically insignificant. Conversely, at the 200 metre threshold the quantile results show a statistically significant (p<.01) increasing pricing effect between the 10th and 95th quantiles – peaking at the 50th quantile coefficient (β = .1468; t = 4.1963, p<.01). This is a similar interpretation for properties located within 400 metres of a rail halts, however the level of the pricing effect incrementally increases for the higher quantiles (at a low level), illustrating that higher priced properties price the amenity of proximity to the rail halts (17.1%) more so than lower priced properties. This is also the case across the pricing distribution for proximal distances from rail hubs at the 600 metre band. At this distance the 5th and 95th quantile prices show the same statistically significant positive effect (16.4%) with

[9] Inter war period (1919-1939)

a less pronounced, albeit more uniform spread across the remaining quantiles. Interestingly, this concave parabola effect evident at the 600 metre distance from rail halts/stations illustrates that both lower and higher priced properties value proximity to rail halts, similarly, arguably due to an amenity effect resulting from urban renaissance and gentrification processes. The findings suggest that this notable disparity between higher and lower priced properties (the extremes) at specific distances clearly indicate how the market prices the economics of rail stations/halts. The economic reality at proximity to access nodes is an economic and social enabler.

Generally the results demonstrate both a vertical inverse parabola effect with distance from rail halts, and a horizontal varied effect across the price distribution at various distances. The findings exhibit the truncation effect for valuing proximity to a rail halt. Overall, examination of the distance effects across each quantile shows a noteworthy trend, whereby up to the 50^{th} quantile the distance bands increase, peaking at the 600 metre distance range, whereas above the 50^{th} quantile they peak at the 400 metre range (**Figure 3**), inferring that slightly higher priced properties are located slightly closer to the rail halts, perhaps explained by closer walking distance without excessive noise pollution. Pertinently, the results show that employing quantile analysis beyond the conditional mean estimates illuminates some important (statistically significant) insights across the price distribution when examining distance to this key public transportation amenity.

<<<Insert Figure 3 Distance to Rail Halts OLS and Quantile coefficients>>>

Examination of proximity to bus stops displays some interesting relationships ‘beyond’ the OLS estimate. The OLS reveals a diminutive and statistically insignificant effect at both the <200 and <400 metre distance bands. When considering the quantiles, two distinctive relationships can be observed. Firstly, at the <200 metre distance, the 5^{th} quantile up to the 50^{th} quantile all show a statistically significant negative relationship between 2.6% and 4.2%, illustrating that lower priced properties are arguably affected by their adjacency to bus stops on main arterial routes. Secondly, at the <400 metre threshold, only the 5^{th} quantile and 95^{th} quantile demonstrate a statistically significant pricing effect of -3.6% and -2.5%, indicating that only the lowest and highest valued properties are impacted by the adjacency to bus stops as a result of an inaccessibility (walking distance). This infers that the economics of transportation friction costs are superseded by the disamenity effect of possible the noise and air pollution implications and distance effects.

Access to Education

Scrutiny of the effect of proximity to both primary and secondary schools further serves to highlight the differential value effects between the mean conditional price distribution and the quantile estimates. The OLS coefficients show the distance effect for proximity to secondary schools to be initially positive (6.1%) and statistically significant with a decay pricing effect evident across the distance bands which become negative at the 800 metre distance band and statistically insignificant. This signifies that adjacency to secondary schools for houses located up to 600 metres has an amenity effect – illustrating the price effect of a good school. In turn, the quantile estimates show differing pricing effects which are considerable at the lower pricing level against higher valued properties both across the price distribution and within each quantile over distance (**Figure 4**). Within a 200 metre radius, properties at the 5th quantile display a 24.9% pricing effect which decreases linearly towards the 90th quantile (β = .0519). This is also generally reflective of the findings evident at the 400 metre distance range, albeit it the pricing effect is not as high (**Table 2**). Indeed, the results show the OLS mean conditional value completely ignore the differential effects clearly impacting on the price distribution. Moreover, at the 600 metre radius, whilst the OLS is insignificant, the quantile results exhibit the lower (5th and 10th) quantiles to still comprise a 6.5% and 4.9% price effect respectively, with the 90th quantile also showing a 2.3% effect. This suggests that particular elements of the market still demonstrate an amenity effect at this distance which suggests that the market rationalises the economics of the ‘catchment effect’ for both the higher and lower valued properties. Interestingly, at the 800 metre range, only the 90th and 95th quantiles show a pricing effect of circa 3-3.7%, inferring that higher priced properties still value secondary schools as a proximal amenity.

<<<Insert Figure 4 Distance to Secondary schools OLS and Quantile coefficients>>>

With regards to primary schools, the OLS coefficients signify an initial negative relationship ($p<.01$) of circa 2% at a distance band of up to 200 metres which diminishes and turns positive up to a distance threshold of 1000 metres (β = .049; t = 2.334, $p<.01$). This shows that proximal distance to primary schools has a preliminary marginal negative pricing effect – perhaps a result of congestion and noise pollution, nonetheless this turns into a positive pricing effect up to a 1 kilometre radius of primary schools (**Table 2**) This is generally consistent with the quantile estimates, however a few noticeable differences exist. Within the

200 metre benchmark, the quantiles all illustrate a marginally higher negative pricing effect (4-5%) compared to the OLS. (**Figure 5**). Moreover, whilst the OLS coefficients are statistically significant for both the 800 metre and 1000 metre distance bands, the quantile analysis only exhibits higher priced properties to show any significance.

<<<Insert Figure 5 Distance to Primary schools OLS and Quantile coefficients>>>

Access to Open Space

When considering the proximity to an area of open space, the OLS and quantile estimates display relatively similar insights as the direction of the pricing effects, commonly negative at the 200 to 600 metre distance band and then becoming positive at the 800 metre or 1 kilometre distance. Nevertheless, the quantile coefficients achieve more statistical significance across particular elements of the price distribution at particular distances. Within 200 metres, the 5th quantile is the only coefficient which shows a negative statistically significant effect (β = -.101, $p<.001$). This infers that lower priced properties in close adjacency to areas of open space observe a disamenity effect, perhaps due to issues pertaining to anti-social behaviour. Indeed, there appears to be a similar picture at the 400 metre distance band. The OLS coefficient is marginally positive and statistically insignificant (**Table 2**), whereas all the quantiles reveal a negative statically significant relationship which is higher at the lower end of the pricing distribution (5th = -.078, $p<.05$). At the one kilometre mark, the OLS shows a statistically significant positive pricing effect of 21.12% (t = 8.875, $p<.01$), alternatively the quantile estimates reveal only the 25th and 95th quantile to be statistically significant indicating a 7.4% and 17.5% positive pricing effect respectively (**Figure 6**). This suggests that at this distance band the OLS is only capturing the effect of higher priced properties which benefit from a 'green' area without suffering proximity disamenity effects whilst being more likely to have private gardens which preclude a reliance on public open space. Generally, the findings clearly show the conditional mean does not capture the more subtle relationships between property pricing and access to open space.

Insert Figure 6 Distance to Public Open Space OLS and Quantile coefficients

Overall, the analysis has illustrated the quantile approach provides some more granular insights as to the specific effects of both structural characteristics of housing and the (dis)amenity effects of proximity to key neighbourhood services. Pertinently, these insights clearly reveal that the nature of the price distribution can have significant effects as to how particular attributes impact on value and equally as important that the OLS conditional mean has a tendency to mis-specify the extent of these effects for certain characteristics. Moreover, the findings highlight that the economic realities of choice selection for higher and lower priced properties for specific neighbourhood characteristics. The deviation of these estimate differentials can be observed in **Table 3**.

<<<Insert Table 3 Summary of variables which depart from the OLS>>>

Conclusions

This paper has applied a quantile regression approach in order to empirically estimate how quantiles of house prices respond differently to a one-unit change in the proximal effects of structural property and neighbourhood characteristics across the conditional distribution of house prices. Utilising quantile regression has permitted the differentiation of the distance effect of particular amenities impacts upon both lower and higher priced properties. The estimates clearly show that the implicit pricing of certain neighbourhood amenities and services varies considerably across the response distribution. This illustrates the existence of quantile effects and that heterogeneous households value neighbourhood characteristics differently, and secondly, it highlights the usefulness of estimating the conditional quantile functions supplementary to the conditional mean. Pertinently, the findings emerging from this research demonstrate that housing and market characteristics are valued differently across the quantile values and that conditional quantiles are asymmetrical. This infers that buyer preferences for locational and specific housing attributes vary significantly for particular determinants which prices the economics of choice selection.

The findings also demonstrate that OLS coefficient estimates have a tendency to over or under specify the marginal mean conditional pricing effects. The findings illustrate that lower priced properties and higher priced properties show different pricing effects which both diminish and proliferate with relation to externalities. This is evident for rail halts which clearly illustrate this effect and moreover highlight this effect changes across the intervening quantiles and with proximity. Indeed, this suggests that at particular quantile levels the proximity to a metro is factored into the economic decision making of a purchaser or not. Moreover, the results present the complex rather than uniform pricing effects across a suite of neighbourhood characteristics. This serves to highlight the varying effects of proximal distances across the pricing distribution. Indeed, the analysis serves to highlight the varying effects of proximal distance upon the quantile coefficients, which reveal negative and positive effects within the distance bands across the price distribution, and pertinently against the mean conditional price estimates generated by the OLS. This is significant for valuers and others concerned with the urban environment in understanding the pricing structure of the housing market in terms of how external neighbourhood characteristics are valued across the entirety of the pricing spectrum.

References

Bayer, P., McMillan, R., and Rueben, K. (2004) *An equilibrium model of sorting in an urban housing market* (No. w10865). National Bureau of Economic Research.

Beyerlein, A. (2014) Quantile regression—opportunities and challenges from a user's perspective, *American journal of epidemiology*, *180*(3), 330-331.

Bourassa, S. C., Cantoni, E. and Hoesli, M. (2007) Spatial Dependence, Housing Submarkets, and House Price Prediction, *Journal of real estate Finance and Economics*, Vol. 35, No. 2, pp. 143-160.

Burnham, K.P. and Anderson, D.R. (2004) Multimodel inference: understanding AIC and BIC in model selection, *Journal of Sociological Methods & Research*, Vol.33, pp. 261-303.

Bolitzer, B. and Netusil, N. (2000) The impact of open space on property values in Portland, Oregon, *Journal of Environmental Management*, Vol. 59, pp. 185-193.

Brunauer, W., Lang, S., & Umlauf, N. (2013). Modelling house prices using multilevel structured additive regression. Statistical Modelling, 13(2), 95-123.

Crompton, J. L. (2001) The Impact of Parks on Property Values: A Review of the Empirical Evidence, *Journal of Leisure Research*, Vol. 33, No. 1, pp. 1-31

Coulson, N. E., & McMillen, D. P. (2007). The dynamics of intraurban quantile house price indexes. *Urban Studies*, *44*(8), 1517-1537.

Cropper, M. L., Deck, L. B., & McConnell, K. E. (1988). On the choice of funtional form for hedonic price functions. *The Review of Economics and Statistics*, 668-675.

Des Rosiers, F., Nolduc, A. and Thériault, M. (1999) Environment and value: Does drinking water quality affect house prices? *Journal of Property Investment and Finance*, Vol. 17, No. 5, pp. 444-463.

Des Rosiers, F., Theriault, M., Kestens, Y. et al. (2002) Landscaping and house values: an empirical investigation, *Journal of Real Estate Research*, Vol. 23(Nos. ½, pp. 139-161.

Dubé, J., Legros, D., Thériault, M., & Des Rosiers, F. (2014). A spatial Difference-in-Differences estimator to evaluate the effect of change in public mass transit systems on house prices. Transportation Research Part B: Methodological, 64, 24-40.

Dziauddin, M. F., Alvanides, S., & Powe, N. (2013). Estimating the effects of light rail transit (LRT) system on the property values in the Klang Valley, Malaysia: A hedonic house price approach. Jurnal Teknologi, 61(1).

Ebru, Ç., & Eban, A. (2011). Determinants of house prices in Istanbul: a quantile regression approach. *Quality & Quantity*, *45*(2), 305-317.

Espey, M. and Owusu-Edusei, K. (2001) Neighborhood parks and residential property values in Greenville, South Carolina, *Journal of Agricultural and Applied Economics*, Vol. 33, No.3, pp. 487-492.

Gloudemans, R.J. (1999) *Mass Appraisal of Real Property*. International Association of Assessing Officers, Chicago, IL.

Gyourko, J., and Tracy, J. S. (1999). A look at real housing prices and incomes: Some implications for housing affordability and quality. *Economic Policy Review*.

Halvorsen, R. and Palmquist, R. (1980) The interpretation of dummy variables in semi-logarithmic equations, *American Economic Review*, Vol. 70, pp. 474-75

Halvorsen, R. and Pollakowski, H.O. (1981) Choice of functional form for hedonic price equations, *Journal of Urban Economics*, Vol. 10, pp. 37–49.

Heckman, J. J. (1980). Sample selection bias as a specification error. *Econometrica, 47, 153-161*

Irwin E. G. and Bockstael, N. E. (2001) The problem of identifying landuse spillovers: measuring the effects of open space on residential property values, *American Journal of Agricultural Economics*, Vol. 83, No.3, pp. 698–704.

Irwin E. 2002. The effects of open space on residential property values, *Land Economics*, Vol. 78, No. 4, pp. 465-480.

Kauko, T. (2003) Residential Property Values And Locational Externalities, *Journal of Property Investment & Finance*, Vol. 21, No. 3, pp. 250-270.

Reich, B. J., Bondell, H. D., & Wang, H. J. (2010). Flexible Bayesian quantile regression for independent and clustered data. *Biostatistics*, *11*(2), 337-352

Liao, S. L., & Chen, J. Y. (2013). Spatial and Temporal Effects of High-speed Rail on House Prices-The Case of Kaohsiung City. 住宅學報, 22(1), 25-54.

Liao, W. C., and Wang, X. (2012). Hedonic house prices and spatial quantile regression. *Journal of Housing Economics*, *21*(1), 16-27.

Kim, H., Park, S. W., Lee, S. and Xue, X (2015) Derterminants of house prices in Seoul: A quantile regression approach, Pacific Rim research Journal, Vol. 21, No. 2, pp. 91-114

Koenker, R., & Bassett, G., Regression quantiles. Econometrica, 1978, Vol. 46,pp.33–50.

Koenker, R., & Hallock, K. (2001) Quantile regression: An introduction.*Journal of Economic Perspectives*, *15*(4), 43-56.

Koschinsky, J., Lozano-Gracia, N., & Piras, G. (2012). The welfare benefit of a home's location: an empirical comparison of spatial and non-spatial model estimates. *Journal of Geographical Systems*, *14*(3), 319-356.

Lancaster, K. J. (1966) A new approach to consumer theory. The journal of political economy, 132-157.

Lutzenhiser, M. and Netusil, N. R. (2001) The Effect of Open Spaces on a Home's Sale Price, *Contemporary Economic Policy*, Vol.19, No. 3, pp. 291–298.

Malpezzi, S. (2003). Hedonic pricing models: a selective and applied review. *Section in Housing Economics and Public Policy: Essays in Honor of Duncan Maclennan*.

Mak, S., Choy, L., & Ho, W. (2010). Quantile regression estimates of Hong Kong real estate prices. *Urban Studies*.

McCord, J., McCord, M., McCluskey, W., Davis, P., McIhatton, D. and Haran, M., 2013. Belfast's iron (ic) curtain: "Peace walls" and their impact on house prices in the Belfast housing market. Journal of European Real Estate Research, 6(3), pp.333-358.

McMillen, D. P. (2008). Changes in the distribution of house prices over time: Structural characteristics, neighborhood, or coefficients?. *Journal of Urban Economics*, *64*(3), 573-589.

Morancho, A.B. (2003) A hedonic valuation of urban green areas, *Landscape and Urban Planning*, Vol. 66, pp. 35–41.

Mueller, J. M., and Loomis, J. B. (2014). Does the estimated impact of wildfires vary with the housing price distribution? A quantile regression approach. *Land Use Policy*, *41*, 121-127.

Murtagh, B., and Ellis, G. (2011). Skills, conflict and spatial planning in Northern Ireland. Planning Theory and Practice, 12(3), 349-365.

Murtagh, B., and Keaveney, K. (2006). Policy and conflict transformation in the ethnocratic city. Space and Polity, 10(2), 187-202.

Newsome, B. A., & Zietz, J. (1992). Adjusting comparable sales using multiple regression analysis-The need for segmentation. *The Appraisal Journal*, *60*(1), 129-133.

Patterson, R. and Boyle, K. (2002) Out of sight, out of mind? Using GIS to incorporate visibility in hedonic property models, Land Economics, Vol. 78, pp. 417–425.

Quang, D. A. and Grudnitski, G. (1995) Golf courses and residential house price: an empirical examination, *Journal of Real Estate and Finance Economics*, Vol. 10, pp. 261-270.

Rosen, S. (1974) Hedonic prices and implicit markets: product differentiation in pure competition, The Journal of Political Economy, Vol. 82, pp. 34-55.

Reed, R. (2013). The contribution of social area analysis: Modelling house price variations at the neighbourhood level in Australia. International Journal of Housing Markets and Analysis, 6(4), 455-472.

Tyrvainen, L. and Miettinen, M. (2000) Property prices and urban forest amenities, *Journal of Environmental Economics and Management*, Vol. 39, pp. 205-223.

Sirmans, S., Macpherson, D., & Zietz, E. (2005). The composition of hedonic pricing models. *Journal of real estate literature*, *13*(1), 1-44.

Sheppard, S. (1999). Hedonic analysis of housing markets. *Handbook of regional and urban economics*, *3*, 1595-1635

Smith, V.K., Poulos, C. and Kim, H. (2002) Treating open space as an urban amenity, *Resource and Energy Economics*. Vol. 24, pp. 107–129.

Song, Y., and Knaap, G. J. (2004) New urbanism and housing values: A disaggregate assessment, *Journal of Urban Economics*, Vol. 54, pp. 218-238.

Xuming, M. and Yicheng, J. (2009) A Study on the Techniques of Mass Appraisal in Real Estate Tax base and Mortgage Valuation based on Quantile Regression, IEEE,

Zhang, L., & Leonard, T. (2014). Neighborhood impact of foreclosure: A quantile regression approach. *Regional Science and Urban Economics*, *48*, 133-143.

Zietz, J., Zietz, E. N., & Sirmans, G. S. (2008). Determinants of house prices: a quantile regression approach. *The Journal of Real Estate Finance and Economics*, *37*(4), 317-333.

EndNotes:

As the symmetry of the absolute residuals yield the quantiles as observed in equation 4;

$$min_{\xi \epsilon R} \sum p\tau(y_i - \xi)$$

where the function $p\tau(.)$ is the tilted absolute value function that yields the sample quantile as its solution. Least squares regression offers a model for how to define conditional quantiles in an equivalent fashion, whereby if the sample $\{y_1, y_2, \ldots, y_n\}$ it may be solved;

$$min_{\mu \epsilon R} \sum_{i=1}^{n} (y_i - \mu)^2$$

The sample mean and the estimate of the unconditional population mean, *EY*, can be obtained. If the scalar μ is replaced with a parametric function $\mu(x_i, \beta)$ and solved;

$$min_{\beta \epsilon R\rho} \sum_{i=1}^{n} (y_i - \mu(x_i, \beta))^2$$

with an estimate of the conditional expectation function $E(Y|x)$ can be obtained.

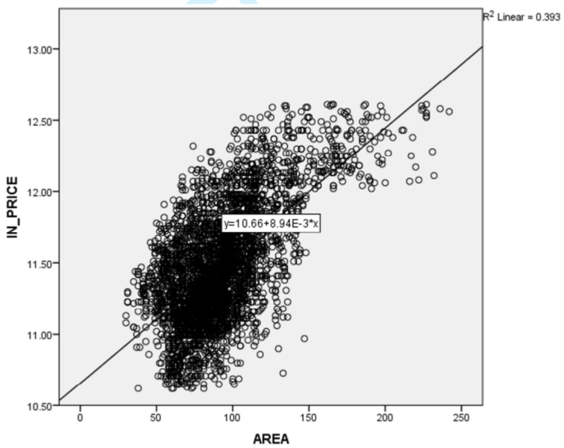
For quantile regression, an estimate of the conditional median function may be obtained by replacing the scalar ξ in Equation (4) with the parametric function $\xi(x_i, \beta)$ and setting τ to ½. To obtain estimates of the other conditional quantile functions, the absolute values with $p\tau(.)$ may be replaced and solved:

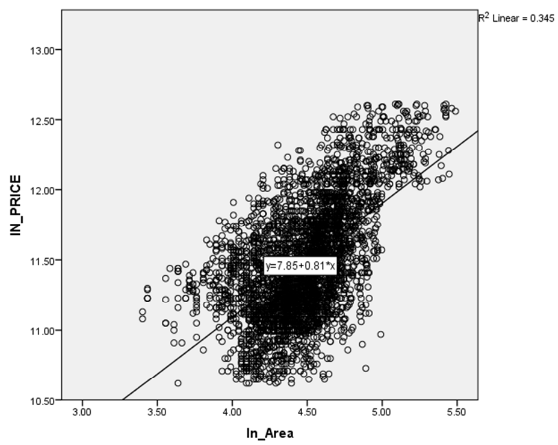
$$min_{\beta \epsilon R \rho} \sum \rho_t(y_i - \xi(x_i, \beta))$$

when $\xi(x_i, \beta)$ is formulated as a linear function of parameters, the resulting minimisation problem solved by linear programming methods. Following the approach of Kim et al. (2015) the bootstrap method as furnished by Buchinsky (1995) is utilised to obtain the standard errors for the coefficients.

Appendix 1

Functional Form





Full OLS Model Description

	B	*t*-stat	Tolerance	VIF
(Constant)	10.906	315.786**		
Size	.007	48.412**	.482	2.074
Apartment	.244	16.852**	.346	2.892
Detached	.327	21.920**	.517	1.933
Semi-detached	.148	16.105**	.455	2.197
Social Built	-.128	-10.546**	.685	1.460
No Garage	-.021	-2.704**	.810	1.235
WARD1	-.091	-2.552*	.603	1.657
WARD2	-.347	-6.643**	.686	1.457
WARD3	-.322	-12.699**	.320	3.121
WARD4	-.287	-7.386**	.508	1.970
WARD5	-.170	-6.820**	.327	3.055
WARD6	-.703	-22.101**	.416	2.402
WARD7	-.226	-6.960**	.360	2.778
WARD8	-.557	-16.277**	.540	1.852
WARD9	-.318	-11.127**	.319	3.134
WARD10	-.462	-14.391**	.523	1.913
WARD11	-.389	-13.960**	.289	3.455

WARD12	.068	2.863**	.470	2.129
WARD13	-.416	-12.842**	.514	1.945
WARD14	-.514	-16.294**	.466	2.146
WARD15	-.335	-10.818**	.350	2.854
WARD16	-.368	-9.895**	.432	2.317
WARD17	-.364	-9.328**	.431	2.322
WARD18	-.227	-6.276**	.386	2.589
WARD19	-.639	-4.883**	.929	1.076
WARD20	-.399	-7.430**	.739	1.352
WARD21	-.161	-3.017**	.749	1.334
WARD22	-.213	-6.705**	.413	2.422
WARD23	-.352	-11.930**	.555	1.800
WARD24	-.466	-14.684**	.467	2.142
WARD25	-.107	-2.775**	.495	2.021
WARD26	-.459	-9.051**	.730	1.369
WARD27	-.250	-7.047**	.415	2.411
WARD28	-.440	-10.426**	.488	2.050
WARD29	-.325	-10.183**	.287	3.479
WARD30	-.396	-12.675**	.437	2.289
WARD31	-.301	-8.016**	.615	1.627
WARD32	-.538	-14.315**	.556	1.798
WARD33	-.127	-4.215**	.462	2.166
WARD34	-.410	-6.899**	.820	1.219
WARD35	-.374	-14.225**	.321	3.118
WARD36	-.290	-12.055**	.296	3.376
WARD37	-.153	-5.187**	.454	2.201
WARD38	-.031	-.967	.317	3.153
WARD39	-.839	-9.793**	.867	1.153
WARD41	-.271	-8.980**	.380	2.630
WARD42	-.020	-.672	.232	4.319
WARD43	-.365	-14.551**	.474	2.110
WARD44	-.411	-10.690**	.445	2.247
WARD45	-.225	-7.739**	.431	2.318
WARD46	-.187	-3.242**	.684	1.462
WARD47	-.371	-9.193**	.493	2.027
WARD48	-.189	-3.676**	.668	1.497
WARD50	-.323	-11.001**	.369	2.710
WARD51	-.591	-11.251**	.680	1.470
WARD53	-.180	-7.044**	.558	1.793
Electric heating	-.023	-1.844	.910	1.098
Gas heating	-.012	-1.628	.909	1.100
Solid heating	.000	.027	.920	1.087
Pre-1919	-.058	-4.377**	.302	3.315
Post-1980	.071	4.447**	.644	1.552
Inter War	.007	.676	.335	2.983

Early Modern	.023	1.749	.637	1.571
MDM Decile2	.004	.215	.263	3.805
MDM Decile3	.079	3.306**	.301	3.321
MDM Decile4	.018	.876	.220	4.542
MDM Decile5	.029	.834	.551	1.816
MDM Decile6	.179	8.418**	.213	4.686
MDM Decile7	.161	7.179**	.265	6.068
MDM Decile8	.202	7.791**	.289	3.462
MDM Decile9	.225	9.550**	.319	4.384
MDM Decile10	.310	11.971**	.310	6.100
Rail<200	-.079	-2.861**	.558	1.792
Rail<400	-.024	-1.030	.468	2.138
Rail<600	-.010	-.514	.467	2.142
Rail<800	-.014	-.813	.423	2.363
Rail<1000	.019	1.401	.432	2.315
CBD<600	.011	.174	.872	1.147
CBD<1000	.269	8.125**	.492	2.034
CBD<2000	-.013	-.936	.744	1.343
CBD<4000	.001	.075	.763	1.311
CBD<5000	-.012	-.608	.794	1.259
Q12014	-.004	-.493	.700	1.428
Q22014	.001	.175	.709	1.410
Q32014	-.009	-1.109	.705	1.419
Sec school<200	.046	2.259*	.771	1.296
Sec school<400	.034	2.632**	.659	1.518
Sec school<600	-.001	-.051	.597	1.675
Sec school<800	-.018	-2.002*	.564	1.773
Sec school>1000	-.019	-1.791	.386	2.593
Pri School<200	-.021	-2.225*	.676	1.478
Pri School<600	.011	1.373	.610	1.638
Pri School<800	.043	3.629**	.529	1.892
Pri School<1000	.071	3.561**	.703	1.423
Pri School>1000	.038	1.439	.478	2.092

Dependent variable: Ln Sale Price; β = unstandardised beta;
**Denotes significant at the 99% level; *95% level.

Collinearity Diagnostics

	Unstandardized Coefficients			Collinearity Statistics	
	B	*t-stat*	*Sig.*	Tolerance	VIF
(Constant)	10.906	315.786	0.000		
beds1	.030	.214	.831	.023	44.402
beds2	.172	1.256	.209	.002	503.586
beds3	.176	1.310	.190	.002	542.132
beds4	.172	1.318	.188	.005	184.922

beds5	.082	.634	.526	.041	24.599
beds6	-.188	-1.344	.179	.177	5.641

Residual diagnostics